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An Information Theory Approach to the Alignment of Images Containing Measurement Inhomogeneity: Application to MR Surface Coil Angiography of the Brain

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Abstract

This paper describes an approach to automatically aligning 3D medical images which contain significant intensity distortion, without the need to correct the distortion. The technique employs a partitioning of space into roughly homogeneous regions over which multi-channel information theory can be used to derive a global measure of image alignment. A multi-resolution iterative optimisation of both alignment and partitioning parameters is employed to recover registration automatically. The technique is applied to the problem of aligning MR surface coil angiography of the brain with a conventional head coil MR image and a CT image.

1 Introduction

Voxel similarity approaches have recently been shown to provide an accurate and robust approach to recovering the spatial alignment between images provided by different 3D medical modalities [3, 2, 7, 6]. In many of these applications typical clinical imaging protocols provide close to spatially homogeneous measurements over the imaged volume. There are however a number of imaging techniques where measurement inhomogeneity over the imaged field becomes significant. This results in shading across an image where the same tissue exhibits different intensities. Shading of this type can cause voxel similarity approaches to fail.

In general a direct approach to spatially aligning non-uniform images is to attempt to correct the spatial variation in measurements [1] prior to alignment with a second image. This may require an accurate model of the field inhomogeneity, and assumptions about differences in the rate of change of image structure and distortion field, and in addition makes no use of information available in the other image. An alternative approach to alignment which we have begun to investigate in earlier work on the alignment of MR and PET images of the pelvis [5], is to introduce additional spatial information into the alignment process.

In this work we have significantly extended the approach by carrying out an iterative optimisation of both alignment and partitioning parameters during the registration. This allows us to apply the approach to automatically recover alignment of surface coil images of the brain where the orientation of the surface coil with respect to the patient is unknown. Surface coils permit localised imaging with greater signal to noise and efficiency than conventional body and head coils. Surface coils do not however provide uniform sensitivity, and thus are most useful when the region of interest is relatively superficial and focal. The sensitivity profile of surface coils makes them less prone to artifacts from distant structures, while providing images of greater resolution than is possible with larger coils. This is put to use in routine clinical imaging of the spine, temporal-mandibular joints, and shoulders, and specialised applications such as MR angiographic imaging of the brain for surgical planning and guidance [4].

In this paper we compare the behaviour of conventional approaches using mutual information, to an approach using measurement encoding along a single axis in the image. Experimental results recovering the alignment of an MR surface coil image of the brain to a conventional anatomical T1 weighted head coil image, and of a simulated MR surface coil image to a CT image are included. In both cases results are compared to an accurate, independent estimate of alignment.

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2 Multi-Channel Mutual Information as a Measure of Image Alignment

Given a pair of images to register and a transformation T mapping one set of measurements onto the other, we can find for corresponding measurements, the values $m \in M$ in image $m(\mathbf{x})$, and values $n \in N$ in a second image $n(T(\mathbf{x}))$. We can calculate the probability of occurrence of individual measurements within the volume of overlap, $p\{m\}$ from the image $m(\mathbf{x})$, and values $p\{n\}$ from the image $n(\mathbf{x})$, and also the probabilities of corresponding pairs of values $p\{m,n\}$.

Mutual information derived from these occurrences of image values has been proposed independently as a measure of alignment for various medical image registration applications by [2] and [3]. The mutual information between a pair of images is derived from the joint and separate probability distributions,

$$I(M;N) = \sum_{m \in M} \sum_{n \in N} p\{m,n\} \log \frac{p\{m,n\}}{p\{m\}p\{n\}}. \tag{1}$$

This can be expressed in terms of the information present in image $m(\mathbf{x})$, $H(M)$, the image $n(\mathbf{x})$, $H(N)$, and the combined image $H(M,N)$. The problem that we face with measurement inhomogeneity is that the same tissues in one or both modalities exhibit different measurement values at different spatial locations.

The measure of mutual information can be directly extended to more than two sources of information, which allows us to introduce additional information about image measurements into the alignment process. Given one MR image with measurements $m \in M$ at spatial locations $\mathbf{x} \in X$, we may partition this space into regions $\mathcal{X} = \wp(X)$, over which coil sensitivity is approximately uniform. We may then encode the measurements within that image with their partition $x \in \mathcal{X}$. The relationship between the M and $\mathcal{X}$ is not a function of the alignment of the two images and so we can use an expression for the conditional mutual information between image values[5] in the distorted image, their partition, and the second image values,

$$I(M,\mathcal{X};N) = H(M,\mathcal{X}) + H(N) - H(M,\mathcal{X},N). \tag{2}$$

The entropies $H(M,\mathcal{X})$, $H(N)$ and $H(M,\mathcal{X},N)$ can be derived from the probability of occurrence of intensities M and N, and partition $\mathcal{X}$ giving,

$$I(M,\mathcal{X};N) = \sum_{m \in M} \sum_{x \in \mathcal{X}} \sum_{n \in N} p\{m,x,n\} \log \frac{p\{m,x,n\}}{p\{m,x\}p\{n\}}. \tag{3}$$

It is important to note that for the purpose of multi-modal alignment each partition need not correspond to regions of completely uniform coil sensitivity. We must simply ensure that tissues which are normally differentiated by undistorted intensities in both modalities, are differentiated from others occurring in the same partition of the image containing the intensity distortion.

In our application we have employed a simple partitioning of space into planes along an axis which can be described by two angles α and β. For a correctly aligned image pair, spatially encoded mutual information between the surface coil image and an undistorted image is maximised when the partitioning axis is normal to the plane of the surface coil as illustrated in figure 1.

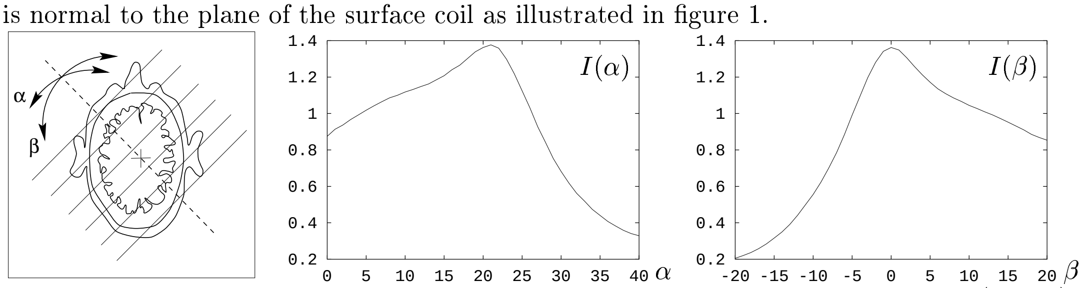

Figure 1: Partitioned mutual information evaluated at different partitioning angles α (centre) and β (right) (in deg.) between an MR head coil image and an artificially distorted version of it.

The registration problem may then be posed as an optimisation of six rigid transformation parameters $T(t_x, t_y, t_z, \theta_x, \theta_y, \theta_z)$ and 2 partitioning parameters α and β to provide the maximum mutual information $I(T, \alpha, \beta)$ between the two images $m(\mathbf{x})$ and $n(T(\mathbf{x}))$. This simple partitioning has the advantage over other approaches such as radial partitioning, in that only two rather than four or more parameters are required.

3 Method

3.1 Alignment of MR Angiography with Other Modalities

Clinically it would be useful to relate T1 weighted anatomical images to the imaged blood vessel structure. The approach with conventional coils used at our site for aligning MR angiography with other modalities is to register the signal intensity image associated with the angiographic image to the second modality. This secondary signal intensity contains significant low contrast anatomical structure, and is acquired simultaneously to (and so in registration with) the angiographic measurements, such images are illustrated in figure 2. In the case of surface coil imaging, both the angiographic and signal intensity image contain significant measurement inhomogeneity.

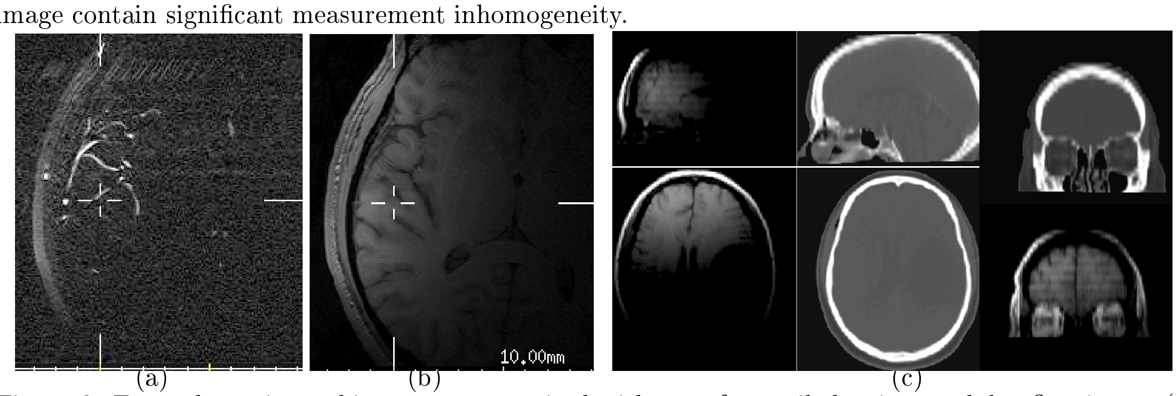

Figure 2: Example angiographic sequence acquired with a surface coil showing modulus flow image (a) and secondary signal intensity image (b) used for registration with other modalities. Axial and sagittal slices through a simulated MR surface coil image for registration with CT (c).

3.2 Experimental Design

In order to compare the behaviour of partitioned and conventional mutual information, two experiments were carried out. To look at the alignment of background surface coil image with conventional T1-MR, a pair of images were acquired of a volunteer using first a surface and then head coil for imaging. Using a 1.5T MR scanner (Philips ACS) we obtained T1/proton density weighted images covering the whole head using the head coil, and the frontal region using a 8.5cm surface coil. Identical 3D gradient echo scans were made of the whole head with imaging parameters: 5.7/13 msec (TE/TR), flip angle of 12^o, and 22cm field of view for voxel dimensions of $0.858 \times 0.859 \times 1.0mm$. The images were acquired using the same geometry and so their measurements were assumed to be spatially corresponding, therefore providing an independent estimate of alignment.

A second set of data was acquired to examine the alignment of surface coil MR with CT of the head. Here, in order to provide an independent registration estimate an MR-T1 CT image pair from the Vanderbilt retrospective registration project [6] was used. An additional surface coil image of a bottle containing a uniform solution of $CuSO_4$ was acquired locally to form a surface coil distortion map. This was then applied as an intensity scaling factor to the Vanderbilt MR image to provide a simulated surface coil image (figure 2).

To estimate the registration transformation, the images were first resampled to $1.5mm$ cubic voxels using a Gaussian kernel to reduce resolution and linear interpolation to increase resolution. Multi-resolution versions of the images were then created using a Gaussian kernel. For a given transformation

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T a discrete estimate of $p\{m, x, n\}$ is evaluated by forming a histogram where measurements in the two modalities are mapped to 32 intensity bins. MR measurements are divided into partition bins, their size and number being determined by the image resolution during the multi-resolution optimisation.

In order to investigate the parameter space provided by conventional and spatially encoded measures we have taken the known alignment of the test image pairs and perturbed the estimate by a random translation of size 20mm and a random rotation of size 20^o. Fifty of these random orientations were then used as starting estimates to the multi-resolution optimisation scheme. The final estimates were then recorded to give an indication of the precision and accuracy.

4 Results

For both the MR-MR and MR-CT pairs, the mean and standard deviation of the displacement of the six alignment parameters from the standard solution are shown in Table 1. When using only intensity values to derive the measure of alignment, for both image pairs the mean estimate is shifted significantly from the true solution, in addition there is a large spread of results around the mean. When using spatial encoding of mutual information the mean estimate is very close to the true solution. For the MR-MR pair, there is a slight shift of the mean away from alignment. This though is of a size appreciably less than the image voxel dimensions. This may have been due to the use of a single axis for encoding, but also may be a result of a slight shift in the position of the volunteer between acquisitions, or small machine dependent errors. For the MR-CT pair the estimate is within the expected accuracy of the independent marker based estimate of alignment.

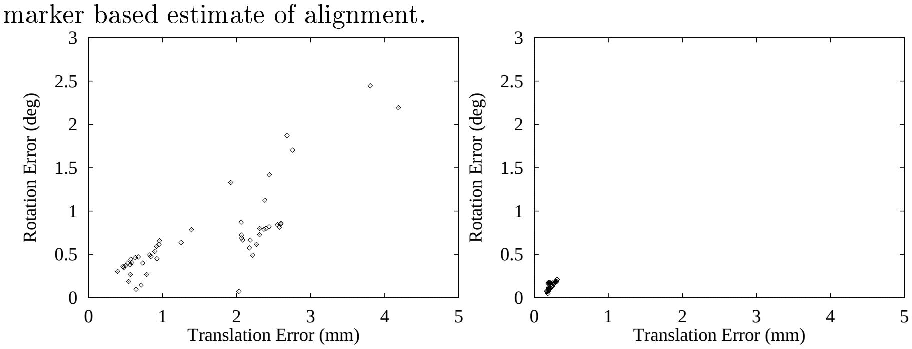

Figure 3: Lengths of translation and rotation error vectors of parameters estimated by mutual information derived from measurements only (left), and from measurements encoded with spatial location (right).

Figure 3 illustrates the solutions found between MR surface and head coil images, from random starts using mutual information derived from measurements only, and from measurements including spatial encoding.

Image Pair	Measure	Translations $t_x mm$	$t_y mm$	$t_z mm$	Rotations θ°_x	θ°_y	θ°_z	Partition α°	β°
MR-MR	$I(M;N)$	0.01(0.31)	-0.44(0.44)	-1.47(0.90)	-0.01(0.31)	-0.35(0.45)	0.16(0.54)	-	-
MR-MR	$I(M,\mathcal{X};N)$	0.17(0.05)	0.13(0.03)	-0.01(0.01)	-0.05(0.02)	-0.11(0.04)	0.05(0.05)	70.8(0.03)	-30.2(0.05)
MR-CT	$I(M;N)$	0.49(0.50)	2.72(2.17)	-0.38(1.98)	-1.91(7.40)	-0.43(0.87)	-0.85(1.18)	-	-
MR-CT	$I(M,\mathcal{X};N)$	0.02 (0.08)	0.07(0.08)	0.32(0.04)	-0.08(0.16)	0.03(0.27)	0.04(0.14)	16.1(0.75)	-110.7(0.60)

Table 1: Mean and (Standard Deviation) of errors in parameters from 50 random starts estimated by mutual information derived from measurements only $I(M;N)$, and from measurements encoded with spatial location $I(M,\mathcal{X};N)$.

5 Discussion

The results using the two image pairs with known alignment indicate substantial improvements in alignment recovery when additional spatial information is introduced into the registration process. Multi-resolution optimisation of both alignment and partitioning parameters appears robust to a clinically typical level of misalignment. In this work we have found that using a single partitioning axis can provide acceptable results. Work is in progress into looking at the use of multiple spatial axes and different geometries for measurement partitioning.

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